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AI and IoT in Nutritional Science: Transforming Digestion Research and Precision Nutrition

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Abstract

This review synthesizes current advancements and applications of these technologies in the context of human digestion and personalized nutrition. The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in nutritional science has transformed dietary monitoring, digestion research, and precision nutrition. AI-driven models, including machine learning and deep learning, enable accurate predictions of nutrient metabolism, glycemic responses, and dietary impacts on health. IoT devices, such as ingestible sensors, wearable trackers, and smart kitchen appliances, facilitate real-time monitoring of food intake, metabolic responses, and digestive processes. These technologies enhance research accuracy, optimize food formulation, and support personalized dietary recommendations. Additionally, IoT-driven automation improves food production and safety, reducing waste and enhancing sustainability. Collectively, these tools have demonstrated the potential to improve dietary adherence, optimize metabolic outcomes, and inform public health strategies. However, challenges related to data security, interoperability, and ethical concerns must be addressed for broader implementation. As AI and IoT continue to evolve, their role in nutritional science will drive innovations in food technology, precision health, and public health initiatives, offering more effective and individualized dietary interventions. Future research should aim to integrate multi-sensor data streams and AI-driven analytics for real-time, adaptive nutrition interventions.

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Abbreviations

AI	Artificial Intelligence
CGMs	Continuous Glucose Monitors
CNNs	Convolutional Neural Networks
EGG	Electrogastrogram
GI	Gastrointestinal
IBFRS	Image-based Food Recognition Systems
ISEs	Ion Selective Electrodes (ISEs)
IoT	Internet of Things
LSTM	Long Short-Term Memory
MAFLD	Metabolic Dysfunction Associated Fatty Liver Disease
ML	Machine Learning
PANI	Pill integrated pH sensors Electrodeposited Polyaniline
SIBO	Small Intestinal Bacterial Overgrowth

Introduction

Gastrointestinal (GI) digestion is a vital biological process that breaks down food into essential nutrients, which the body absorbs and uses for energy, growth, and cellular repair. Digestion begins in the mouth with the breakdown of food, journeys through the stomach and intestines by way of digestive enzymes and fluids, and concludes in the small intestine, site of most nutrient absorption. Digestion is the process that provides nutrient molecules into the cells; therefore, proper

Digestion is the very beginning step in sustaining our health. Conversely, digestive irregularities can lead to malnutrition, GI conditions, and other diseases. Healthcare providers and researchers need to have a deep understanding of this process. Advances in technology, particularly advances in Artificial Intelligence (AI) and the Internet of Things (IoT), are providing cutting-edge new insights into gastrointestinal digestion. These platforms are paving the way to transformative research and customized diets that can revolutionize public health and consumer behaviour.

In real-world applications, AI is increasingly being used to support dietitians in dietary planning, weight management, and malnutrition prediction. For instance, virtual nutrition assistants like chatbots have demonstrated up to 97% accuracy in diet-related queries and have shown potential in facilitating behavioral change in users.[1,2] AI-based tools are also being tested to assess nutritional knowledge, achieving more than 74% accuracy in simulating dietitian responses.[3] This review aims to critically analyze the integration of AI and IoT in digestive health monitoring and personalized nutrition.

Discussion

Transforming Nutritional Research Through AI and IoT

AI and IoT are reshaping the field of nutritional science by enhancing the precision, personalization, and efficiency of data collection, analysis, and application. These technologies are driving innovative approaches to better understand dietary habits and health outcomes.[4]

Artificial Intelligence (AI)

AI uses advanced technologies such as natural language processing, machine learning, and computer vision to imitate human-like intelligence.[5,6] In nutrition research, AI helps in processing a large amount of data to predict deficiencies in nutrients and customize dietary plans.[7] Machine learning models can be used to incorporate the dietary data with information about any patient's microbiome, genetics and lifestyle in order to customize the nutrition strategies that help promote optimal health.[8]

AI also provides insights into the complex relationships between diet, the gut microbiome, and metabolic health.[9] In clinical settings and public health initiatives, these findings are proving to be extremely beneficial in the design of treatments that attempt to improve the nutritional outcomes of both people and communities.

Internet of Things (IoT)

With the use of IoT, smart devices can continuously monitor and transmit real-time data, enabling incredibly accurate tracking of metabolic responses, physical activity and eating habits. In case of nutrition, wearable fitness bands, biosensors, and smart kitchen appliances can be included as IoT devices.

These devices provide near-perfect dietary assessments. Studies have shown that fitness trackers that are worn on the wrist or leg can be used to monitor the physical activity and record various parameters including blood glucose levels, whereas smart kitchen gadgets help in tracking the consumption of food and reduce food wastage.[10] Researchers and individuals alike are empowered by this constant flow of data to make better, faster decisions on their diet and well-being.[11]

The synergy between AI and IoT

When AI and IoT are combined together, a powerful partnership is developed that helps in enhancing the nutritional science. This synergy can manage complex databases, process data in real time, and provide personalized dietary recommendations. Researchers benefit from advanced tools to analyze how diet impacts health, while individuals receive tailored guidance to manage their nutrition effectively. By leveraging these cutting-edge technologies, the future of nutritional science is poised for tremendous advancements not only in research capabilities but also in empowering individuals to make smarter, healthier dietary choices every day.

Predicting Protein Breakdown with Machine Learning

Protein hydrolysis plays a significant role in analysing the nutritional quality. Conventional methods used for studying hydrolysis of protein are often time-consuming and labor-intensive. Machine learning (ML) is developing this process by providing a quicker and more accurate prediction.

To produce accurate predictions, Machine Learning algorithms make use of datasets that include details like digestibility parameters, enzymatic conditions, and amino acid sequences. For example, decision tree algorithms and neural networks can mimic in vitro protein hydrolysis, greatly reducing the need for repeated trials.

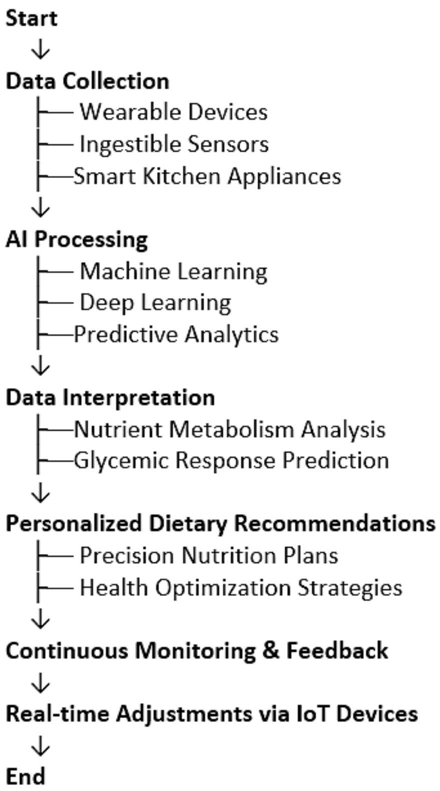

Fig. 1: AI-powered insights into macronutrient digestion

Furthermore, the reactions of various protein sources, whether generated from plants or animals, may be examined by these models in relation to processing parameters such as heat or pH variations. In order to create customized formulations that satisfy certain dietary requirements, factors that either hinder or enhance the breakdown of proteins, such as anti-nutritional substances or additional additives, are additionally taken into account by advanced systems. Artificial Neural Networks (ANNs) have been extensively used in modeling non-linear nutritional datasets for food composition studies, such as classifying orange juice origin with over 92% accuracy and analyzing whey protein profiles in human vs. bovine milk.[12] AI has also been applied in bitterness prediction of peptides, micro-mineral profiling in vegetables, and evaluating nutrient retention during food processing using advanced ML algorithms like GA-RBFN, SVR, and LS-SVM. These approaches significantly reduce the time and cost of food analysis while increasing prediction precision.[13-16]

This AI-driven approach saves time, resources and also enhances the customization of protein products to diverse needs, from athletes seeking quick amino acid absorption to individuals with digestive challenges.[17] By combining these machine learning models with Internet of Things-enabled devices, further verification of results in practical contexts may be achieved, thereby facilitating the development of incredibly precise and customized dietary solutions.

AI in Monitoring Carbohydrate Digestion And Glycemic Responses

During digestion, complex carbohydrates must be broken down into simple sugars, which has an immediate effect on blood glucose levels. Observing the glycemic responses is significant for people trying to manage diabetes and other metabolic disorders. AI can be used to predict the pattern of change in blood sugar level after meals, by analyzing the information from continuous glucose monitors (CGMs).[18]

AI helps in assessing the glycemic index of various foods, detect abnormalities and recommend dietary adjustments, by analysing the fluctuations in blood sugar.[19] Additionally, the differentiation between quickly digestible starches and slower-digesting polysaccharides can be achieved by machine learning models, aiding in the development of low-glycemic food options. The digestion of lipids is recognized as a multifaceted process that involves emulsification, enzymatic breakdown by lipases and the absorption of fatty acids and glycerol.

Studies include image-recognition systems powered by AI, in which users upload meal photos for analysis. These tools determine the carbohydrate content and analyse the glycemic impact depending upon the portion size and carbohydrate content.[20,21] AI-powered Image-Based Food Recognition Systems (IBFRS) automate food-intake monitoring and convert photographic observations into nutrient estimates, improving accuracy over conventional recording methods.[22] In this study, deep learning models such as Convolutional Neural Networks (CNNs) were used to classify food items from images and their nutrient values were evaluated.[23] IBFRS could estimate the glycemic index (GI) of meals, helping in personalized dietary recommendations. However, errors in portion estimation and the complexity of mixed ingredients are challenges that necessitate further modifications to AI algorithms.[24]

AI methods such as machine learning and deep learning are also replacing traditional dietary recall methods. In one study, an AI app called COCO Nutritionist showed nutrient estimation almost equivalent to the gold-standard 24-hour recall, with macronutrient predictions within ±1% accuracy.[25] Similarly, large datasets like NHANES were used in ML models to predict cardiovascular risk using nutrient intake data, with AUROC values as high as 0.82, indicating high prediction accuracy.[26]

Deep Learning Advancing Lipid Digestion Research

Traditional methods of studying lipid digestion have relied heavily on in vitro models or animal trials, which struggle to fully mimic human physiology. The game is now being changed by deep learning through the use of datasets on lipid structure, emulsification properties and enzyme activity to simulate digestion processes. These advancements are not only refining drug delivery systems that are reliant on lipids but are also helping to fortify foods with essential fatty acids, ultimately leading to improvements in dietary recommendations for better health outcomes.[27]

One major application is predicting how innovative lipid formulations such as structured lipids will behave during digestion. Tools such as CNNs and Long Short-Term Memory (LSTM) networks have been used to interpret electrogastrogram (EGG) signals. These non-invasive signals provide valuable insights into gut motility during lipid digestion.[28]

Deep learning has a significant role in advancing lipid digestion research, especially in understanding the metabolic dysfunction associated fatty liver disease (MAFLD). Researches have shown how machine learning in association with lipidomics help in identifying biomarkers that cause progression of MAFLD. These deep learning models can analyze vast data of lipidomics to decode the pattern, classify the lipid profiles, which are not that effective through conventional methods. Furthermore, deep learning enhances the integration of multi-omics data, refining metabolic pathway analysis and providing a deeper understanding of lipid-mediated mechanisms in liver disease.[29] These advancements are not only refining drug delivery systems that rely on lipids but also helping to fortify foods with essential fatty acids, ultimately improving dietary recommendations for better health outcomes.[30] Deep learning approaches like CNNs are revolutionizing dietary assessments by enabling image-based macronutrient and portion size estimation, significantly outperforming hospital staff in malnutrition prediction. One AI tool demonstrated <15% error in macronutrient prediction compared to >30% by nurses.[31]

ANN models have been employed in optimizing production of bioactive nutrients like retinyl laurate, phycobiliproteins, and benzoquinones—compounds with anti-tumor and immunomodulatory potential. These models, sometimes combined with evolutionary techniques like genetic algorithms (GA) or fuzzy logic methodologies (FLM), enable complex nonlinear optimization for nutrient synthesis.[32] This demonstrates how AI tools are not only analytical but also play a functional role in nutrient formulation.[33-35]

Real-Time Monitoring Of Digestion Using Iot Devices

Smart Sensors For Tracking Gastrointestinal Ph and Enzyme Activity

The gastrointestinal (GI) tract is a highly dynamic environment where fluctuations in pH levels and enzyme activity play a critical role in digestion and nutrient absorption. To better understand these processes, researchers have developed ingestible capsules equipped with smart sensors. These tiny devices are fitted with pH sensors, enzyme activity detectors, and wireless transmitters. Once swallowed, they travel through the digestive system, continuously transmitting data about pH levels and enzymatic activity at different stages of digestion.

Researchers explored a novel autonomous ingestible smart biosensing system in pill format designed for real-time monitoring of gastrointestinal (GI) pH levels. These pH levels are correlated with gastrointestinal disorders such as inflammatory bowel disease (IBD), ulcerative colitis, and pancreatitis. A smart sensing pill integrated with pH sensors based on PANI - electrodeposited polyaniline on carbon-coated conductive threads was developed, which offered a high sensitivity in detecting change in pH level as it passes through the GI tract. With the dimensions of 22.1 mm in length and 9 mm in diameter, the smart pill was designed for efficient *in vivo* operation.[36-38]

Recent advancements in biosensing technology have facilitated the real-time assessment of biochemical markers in the gastrointestinal (GI) tract, providing critical insights into how diet composition influences digestive processes and gut health. A study utilizing Ion Selective Electrodes (ISEs) demonstrated the direct sensing of ammonium ions in gastrointestinal digesta samples, establishing a correlation between dietary protein digestibility and protein fermentation in the gut. By modulating the protein quality in pig diets, researchers observed a significant increase in ammonium ion concentration increasing from 180 ppm to 400 ppm in the proximal colon when consuming poorly digestible proteins, compared to diets based on easily digestible proteins. These findings highlight the impact of dietary composition on gut microbiota activity and metabolic byproducts, reinforcing the role of nutrition in digestive health. Moreover, the use of potentiometric sensors for in vivo-like detection of ammonium ions represents a promising approach for non-invasive gut analysis. When integrated with AI-powered platforms, such biosensing data can be analyzed in real-time, enabling advanced pattern recognition and predictive modeling to explore the relationship between dietary habits, enzymatic activity, and gut-brain axis interactions. This AI-driven approach enhances the potential for personalized dietary recommendations and targeted treatments for digestive disorders by identifying trends and metabolic responses specific to individual gut microbiomes.[39-44]

Wearable Devices for Monitoring Glucose Levels and Analyzing Dietary Intake

Wearable technology, such as continuous glucose monitors (CGMs), has become an invaluable tool for people with diabetes, allowing them to keep track of their blood sugar levels in real time. These IoT-enabled devices synchronize with mobile applications, giving users instant insights into how their meals affect their glycemic response. By analyzing these patterns, advanced AI systems can suggest dietary adjustments customized to the individual's needs.[45,46]

Beyond glucose tracking, researchers are integrating additional dietary analysis features into wearable devices. Wearable technology is advancing beyond glucose tracking by integrating dietary analysis features, linking food intake with real-time metabolic responses. A study using continuous glucose monitoring (CGM) and wearables tracked 2,217 participants' glucose levels, diet, and activity, providing personalized insights via a smartphone app. By overlaying glucose fluctuations with meal data, macronutrient breakdown, and glycemic index (GI), the system enabled tailored lifestyle recommendations. This aligns with emerging food recognition apps, which estimate calorie and nutrient intake, helping users understand how diet impacts glucose stability. Such AI-driven solutions promote personalized nutrition, metabolic health improvement, and Type 2 Diabetes prevention.[47-49]

The future of these technologies lies in multi-sensor platforms that monitor not just glucose levels, but also parameters like heart rate, physical activity, and gut motility, giving a more comprehensive view of metabolic health.

Advanced Techniques in Nutrient Digestion Research with IoT

The integration of IoT technology in nutrient digestion research has significantly enhanced the study of digestive processes by enabling real-time data collection and analysis. Ingestible capsules and smart sensors track key parameters such as pH levels, temperature, pressure, and nutrient concentrations within the gastrointestinal (GI) tract, providing researchers with valuable insights into nutrient release patterns and the influence of food composition, portion sizes, and digestive health. These devices also aid in diagnosing digestive disorders like gastroparesis and small intestinal bacterial overgrowth (SIBO), contributing to more personalized dietary and therapeutic solutions.[50] Additionally, IoT-enhanced in vitro digestion models allow for precise control and monitoring of experimental conditions, facilitating high-throughput studies on nutrient bioaccessibility and food matrix effects. Automated bioreactors equipped with IoT sensors help simulate real-life digestive conditions, improving food formulation and nutrient delivery through AI-based predictive models. Furthermore, IoT-driven real-time data collection, using wearable devices and ingestible sensors, enhances nutritional research by offering objective insights into eating habits, digestive health, and metabolic responses.[51] This eliminates the inaccuracies of self-reported food diaries and enables more precise, personalized dietary recommendations, transforming the field of nutrition science.

Future Directions - Merging AI, IoT, and Nutritional Science

The integration of AI and IoT into nutritional science is revolutionizing how dietary data is gathered, analyzed, and applied, paving the way for more precise and personalized health solutions.[52] AI-driven precision nutrition tailors dietary recommendations based on an individual's genetic makeup, metabolism, and microbiome, optimizing health outcomes through targeted interventions. IoT devices, including fitness trackers and smart kitchen appliances, facilitate real-time dietary monitoring, offering continuous insights into eating habits and lifestyle choices. Predictive analytics powered by AI further enhances nutrition science by forecasting health outcomes and enabling early interventions. Innovations in food science, such as AI-powered automated nutritional analysis and IoT-enabled smart packaging, improve dietary tracking, food safety, and waste reduction.[53-57] AI and IoT also optimize food production by monitoring environmental factors to enhance crop yields and food quality.[58-60] The evolution of AI-driven systems may soon lead to the development of global nutritional monitoring networks that adapt to regional dietary habits and gut microbiota profiles. Certain platforms could personalize nutrient recommendations in real time and bridge biomedical, clinical, and epidemiological data through interconnected systems.[61] However, challenges remain, including data privacy concerns, integration issues across multiple platforms, and ethical considerations related to algorithmic biases and transparency. Despite these hurdles, the future holds exciting opportunities, from highly personalized nutrition plans and improved public health initiatives to the development of innovative food products tailored to specific health needs and consumer preferences.[62] Several other applications of AI in nutritional sciences is detailed in Table 1.

Table 1: Applications of AI in nutritional sciences

AI Technology Used	Application in Nutrition Science	Key Features & Findings
SVM-based Food Intake Measurement System	Automated food intake monitoring	Uses support vector machines (SVM) for classifying food items based on extracted features from images with an accuracy of 78.5% on PFID dataset.[63]
Depth Camera-based Food Intake Estimation	Volume-based dietary assessment	3D modeling technique estimates portion sizes with high precision using a structured light depth camera with an error rate of ±6.4% in volume estimation.[64]
Fuzzy Clustering & Whale Neural Network	Food recognition and calorie estimation	Uses hybrid AI models for clustering and classification, improving segmentation of food images with an accuracy of 83.2%.[65]
AI System (goFOOD™)	AI-assisted dietary tracking	Mobile app using deep learning for real-time food recognition, trained on Food-101 dataset with an accuracy of 92.6%.[66]
Multi-task CNN	Food constituent estimation	CNN-based model predicts nutritional content, useful for managing lifestyle diseases with a Macronutrient estimation error of ±5.8%.[67,68]
Neural Network Classifier & Image Segmentation	Automated dietary assessment	AI-enabled calorie calculator using deep learning segmentation with the segmentation IoU of 87.5%.[69]
Digital Technology in Clinical Nutrition	AI-powered diet tracking	Integrates AI for clinical dietary management and personalized nutrition plans and it showed a 15% improvement in diet adherence.[70]
Digital Photography with AI	Dietary assessment for special populations	AI-assisted image recognition for tracking food intake in overweight individuals and found to have an error rate of ±8.1% in calorie estimation.[71]

AI Driven Dietary Platforms in Precision Nutrition

Several AI-driven dietary platforms are emerging as practical applications of computational nutrition science. Viome employs metatranscriptomic sequencing to capture active microbial pathways within the gut microbiome, thereby enabling highly personalized dietary recommendations that target host–microbe interactions and metabolic health.[72] PhyteByte, a machine learning based computational tool, predicts the bioactivity of food-derived compounds by leveraging pharmacological datasets such as ChEMBL and linking predicted compounds to food sources through FooDB. This supports the identification of nutritionally relevant bioactives with drug-like effects for use in precision diets and nutraceutical development.[73] In parallel, goFOOD™ provides an AI-powered smartphone application that incorporates deep learning for food recognition, segmentation, and three-dimensional volume estimation to assess caloric and macronutrient intake from images or videos, with demonstrated accuracy across more than 300 food categories and clinical usability for dietary monitoring.[74] Collectively, these platforms illustrate how AI and IoT-enabled solutions are transitioning from theoretical models into actionable tools that advance personalized nutrition and real-time dietary assessment.

Ethical Concerns in AI and IoT Applications

The integration of AI and IoT in nutritional science raises critical ethical concerns, particularly regarding data privacy, algorithmic bias, and informed consent. Devices such as wearable trackers and ingestible sensors collect sensitive physiological and behavioral data, necessitating stringent data governance frameworks to protect user confidentiality. Additionally, AI models trained on non-representative datasets may produce biased dietary recommendations, potentially disadvantaging certain populations. Although chatbots and AI diet planners are accessible tools, users often misinterpret their recommendations. Studies have shown that AI systems occasionally failed to detect allergens or provide warnings for unbalanced meals, raising concerns about patient safety and misinformation.[75] Ensuring transparency in algorithm design, securing user consent for data use, and fostering equitable access to AI-driven nutrition technologies are essential steps to uphold ethical standards in this rapidly evolving field.[76]

Conclusion

The integration of artificial intelligence (AI) and the Internet of Things (IoT) in nutritional science is reshaping how dietary data is monitored, analyzed, and applied in both clinical and consumer contexts. Numerous studies reviewed in this article demonstrate how AI models such as convolutional neural networks (CNNs), long short-term memory (LSTM) models, and ensemble machine learning algorithms have been effectively applied to predict postprandial glycemic responses, analyze macronutrient intake with over 90% accuracy, and personalize diet recommendations using real-time biosensor inputs. For instance, AI-driven dietary platforms like Viome, PhyteByte, and goFOOD™ have shown promising outcomes in tailoring nutrient intake and predicting metabolic responses based on individual gut microbiota, genetic profiles, or continuous glucose monitoring (CGM) data.

Viome works on the meta-transcriptomic analysis of gut microbiota in combination with AI models to provide personalized nutrition strategies. PhyteByte applies machine learning to identify bioactive compounds in foods with pharmacological potential, bridging the gap between food chemistry and individualized health outcomes. goFOOD™ is an AI-powered mobile app that enables real-time dietary assessment. These examples illustrate how commercial and research-driven tools are advancing precision nutrition by tailoring dietary recommendations.

Parallel advancements in IoT including ingestible sensors, wearable trackers, and smart kitchen systems have enabled continuous, real-time monitoring of digestion-related biomarkers such as pH, ammonia, and CO_2 levels. These devices contribute to a more granular understanding of nutrient bioaccessibility and gastrointestinal function under real-life conditions.

However, across many studies, limitations persist. Common biases include over-reliance on small, homogeneous datasets, lack of longitudinal validation, and insufficient representation of diverse population groups. Furthermore, integration across platforms remains technically challenging, and ethical concerns regarding data privacy and algorithmic transparency are not yet fully addressed.

Despite these challenges, the convergence of AI and IoT holds significant promise for the future of precision nutrition. This review highlights the growing body of evidence supporting their use in disease prevention, individualized dietary planning, and metabolic optimization. As interdisciplinary technologies mature and data governance frameworks evolve, these innovations are expected to deliver more accurate, culturally inclusive, and clinically actionable nutrition solutions on a global scale.

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This research does not involve any clinical trials.

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Author Contributions
- **Poojitha Pushparaj:** conceptualized the study, designed the research framework, and supervised the overall project execution.
- **Lakshmi Mohan:** contributed to the literature review and data analysis related to AI-driven nutritional research.
- **Anju Kanicheril Ambikalekshmi:** responsible for collecting and analyzing data on IoT applications in digestion monitoring.
- **Elsa Cherian:** assisted in drafting the manuscript and compiling references.
- **Rosamma Rajan:** contributed to experimental design and interpretation of findings in nutritional science.
- **Nandha Kumar:** provided technical expertise in machine learning models and statistical validation.

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